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Artificial Intelligence based Assisted Computational Analysis of Micropolar Hybrid Nanofluid Flow with Non-Fourier Heat Flux and Thermal Radiation Effects

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ABSTRACT

In this study, a hybrid artificial intelligence and computational fluid dynamics (AI-CFD) method is used to study the thermal-flow behavior of micropolar CuO-Ag/water hybrid nanofluids under magnetohydrodynamic (MHD) mixed convection over a vertical porous plate with non-Fourier heat flux effects. Thermal transport phenomena are modeled accurately by the mathematical model, which includes the effects of thermal radiation, joule heating, viscous dissipation, suction/injection, heat generation/absorption, and cattaneo–christov heat flux. Similarity transformations are used to reduce the governing nonlinear partial differential equations to a dimensionless system of ordinary differential equations (ODEs) which can then be numerically solved by the Runge-Kutta fourth-order (RK4) method with the

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shooting technique. A data-driven machine learning framework was designed based on synthetic data generated from numerical solutions to improve the predictive capability and to minimize computational complexity. The supervised learning algorithms implemented were Linear Regression, Random Forest Regressor, Artificial Neural Networks (ANNs) using Python based TensorFlow/Keras and Scikit-learn libraries. To enhance the stability and accuracy of the model, data preprocessing and feature normalization techniques were used. The ANN model showed better performance with a maximum $R^2 = 0.984716$ for velocity prediction and $R^2 = 0.993335$ for temperature estimation, better than conventional regression models. The numerical analysis shows that raising the values of thermal radiation, Eckert number, and nanoparticle volume fraction, the temperature profiles and thermal conductivity are significantly improved, while the effect of the magnetic field is decreased the fluid velocity. Proposed AI-assisted surrogate framework is suitable for capturing nonlinear thermo-fluid interactions in an efficient manner and provides a computational efficient alternative for predicting heat transfer characteristics in advanced thermal engineering systems. The results show the promise of applying machine learning to numerical fluid dynamics for smart thermal management, energy system, and new heat transfer applications..

Keywords: Artificial intelligence; Machine learning; Computational fluid dynamics; Hybrid nanofluids; Non-Fourier heat flux; Micropolar fluid; Thermal radiation; Artificial neural networks; Magnetohydrodynamics; Heat transfer enhancement.

1. Introduction

In the fields of biomedicine, engineering, and energy production, among others, there is a remarkable understanding of nanoscience to bring the thermal agitation close to the sources to the highest possible speed [1]. The increased interest has led to studies of "nanofluids," which are fluids with nanoscale particles to help reduce the thermal properties. Hybrid nanofluids are the ones created by mixing various nanoparticles in a base fluid which provide increased thermal properties due to the increased thermal interactions and larger surface area, and are suitable for use in microelectronics, cooling systems, energy industry such as nuclear reactors and plasma research [2]. Although a lot of progresses are made in the study of

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thermophysical properties of hybrid nanofluids, hybridization with machine learning (ML) techniques offers new opportunities to develop predictive models. Through analyzing the complex interactions and optimizing the thermophysical properties by ML algorithms, researchers can improve the prediction of temperature, velocity, and concentration in fluid flow systems [3]. This study has suggested a hybrid model by incorporating the traditional heat transfer methods and ML to accurately predict the nature of flow of micropolar composite nanofluid (CuO-Ag in water) over a vertically oriented plate to generate synthetic data from the known physical equations to enhance the accuracy of the prediction and understanding of the heat transfer characteristics [4]. Das, P. K., et al. [5] studied heat transfer between a flat tube with a hybrid Nanofluid, and Malviya, K., et al. (2024). In [6] the effect of carbon nanotubes (CNTs) on a water based hybrid nanofluids was studied. Algehyne et al. [7] and Akbar et al. [8] investigated the entropy generation and heat radiation of nanofluids, and Baithalu et al. [9] came up with the concept of dispersing nanometer-scale particles in conventional fluids. Balaji, T., et al.[10] formulated nanoparticle preparation techniques and analyzed their thermophysical properties. Plant, R. D., et al. [11] investigated the flow behavior of silver and copper nanofluids over a Riga plate Research Das, P. K., et al.[5] has emphasized the improved heat transfer capabilities of nanofluids, while hybrid nanofluids, which combine multiple nanoparticles, have emerged as more effective because of their enhanced thermal conductivity and stability. Banerjee, A. and R. Barua [12] analyzed hybrid nanofluids flowing over permeable surfaces while Plant, R., et al. (2021). [13] examined the impact of nonlinear thermal radiation in CuO-Al2O3/water hybrid nanofluid flow. Ali, B., et al. (2024) [14] explored heat transfer in dusty and hybrid dusty nanofluids, and several foundational studies Jeelani, M. B., et al. [15] and Raju, A., et al. [16] explored hybrid nanofluids in thermal applications. The micropolar fluid theory, first proposed by EL-Hakiem, A., et al.[17], enhances the classical Navier-Stokes equations by considering particle micro-rotation, a concept explored by Algehyne, E. A., et al. [7] in stretched sheet heat transfer. Ali, B., et al. [14] did further study on micropolar fluid and MHD flow in porous material. Some recent studies, such as those of Ali, F. A. and A. M.

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Alsaffawi [18] have investigated nanofluids with vertical plates including applications of Casson fluids and Brinkman nanofluids. The demand for efficient heat transfer has been rising across different industries and in recent years, there has been growing interest in the use of hybrid nanofluids, which combine the thermal properties of two or more different types of nanoparticles, such as Al2O3-water and CuO-water nanofluids, and exhibit better thermal performance as compared to both water-based and oil-based nanofluids [19] for the use in microelectronics, cooling systems and biomedical applications [20] and [21]. Although significant efforts have been made to understand thermophysical properties of hybrid nanofluids, Vishalakshi, A., et al. [22] noted that there was a scope to integrate machine learning (ML) into the predictive model. For complex interactions in nanofluids, ML has been found to be useful as shown by Ibrahim, W. et al. [23] and Khan, U. et al. [24] in optimizing the thermophysical properties of the nanofluid depending on the various operating parameters. For example, using ML algorithms, researchers such as [25] and [26] have made better predictions of the temperature, velocity and concentration in fluid systems, which has resulted in better material design and system efficiency. Significant potential has been shown in recent advancements of using artificial intelligence and data-driven modeling to solve nonlinear thermo-fluid problems with a lower computational cost. Although the traditional numerical methods like RK4 and shooting techniques give very accurate solutions, they usually involve simulations to be repeated for different parametric configurations, resulting in higher processing time and complexity. Machine learning (ML) approaches are more efficient, as they learn hidden non-linear relationships directly from numerical datasets and predict thermal-flow characteristics with fast speed without needing to repeatedly solve the governing differential equations.

In the field of fluid mechanics and heat transfer, ML models have now come into use in surrogate modelling, parametric optimization, and intelligent prediction of other engineering responses like velocity gradients, thermal boundary layers, skin friction coefficients, and Nusselt numbers. Inspired by these advances, the current research combines the physics-informed machine learning and computational fluid dynamics methods to develop a physics-informed predictive model for micropolar

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hybrid nanofluids subjected to non-Fourier heat flux regime.

The proposed framework uses the transformed governing equations to create synthetic datasets as opposed to numerical ones and trains multiple regression-based learning models to approximate nonlinear thermal-flow behavior. This integration not only boosts the predictive accuracy but also showcases the potential of using AI for optimizing thermal systems in complex engineering scenarios. Based on the suggestion of Alizadeh et al. [27], to make more accurate prediction of the behavior of micropolar hybrid nanofluid (CuO-Ag/water) over a vertical plate, this study proposes a hybrid model, which is an integration of traditional heat transfer methods with ML.To improve the accuracy and the understanding of heat transfer behavior, and to generate synthetic data that can be used in the prediction of the behavior of micropolar hybrid nanofluid (CuO-Ag/water) over a vertical plate, this study proposes a hybrid model, which is the integration of traditional heat transfer methods with ML. Magnetohydrodynamics (MHD), the study of the behavior of a fluid when subjected to magnetic and electromagnetic forces, has been widely used in fields such as boilers, solar panels and polymers. The squeezing flow of a micropolar liquid under the effect of a magnetic field has been studied by Zuhra, S., et al. [28] and the heat transfer study in the presence of magnetic field for nano fluids has been done by Khan, U., et al. [29] and Bilal, H. M., et al. [30]. The previous studies [31, 32, 33] studied the effect of operation parameters such as Reynolds number, nanoparticle volume fraction and slip effects, however the effect of multi-slip on magnetohydrodynamic mixed convection with non-Fourier flux has not been studied. The slip effects in unsteady MHD flow with heat and mass transfer between a permeable sheet were discussed by Shahzad, A., et al. [34] where numerical solutions were obtained using the shooting method and the physical parameters were analysed. Further, regression analysis with the aid of ML models gave valuable insights for the prediction of flow characteristics, thereby further improving the understanding of skin friction coefficient and the Nusselt number.

The purpose of this work is to examine the hydrodynamic and thermal characteristics of hybrid nanofluids under the MHD conditions with the implications of varying the nanoparticle shapes and concentrations. This study not only provides

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insights into the dynamics of nanofluids through experimental methods but also offers a computational framework to further deepen the understanding of these systems, thereby improving their application in thermal management systems.The present study investigates the thermal and flow performance of micropolar hybrid nanofluids (CuO-Ag/water) by using machine learning and non-Fourier heat flux models. It is intended to explore the main parameters which affect heat transfer and fluid flow, including suction/Injection, Thermal radiation and magnetic fields. Machine learning techniques are incorporated to improve the accuracy of the predictions. The results indicate that the thermal performance of the hybrid nanofluids is considerably enhanced and give insights on how to optimize thermal management in different applications.

The novelty of the present work is the unification of the non-Fourier heat flux model, the dynamics of micropolar hybrid nanofluid, and machine learning-based predictive analysis in a single computational framework. In contrast to previous research that were confined to numerical simulation, this research proposes a thermo-fluid modelling approach which combines artificial intelligence with numerical simulation that is able to predict the heat transfer behavior with higher computational efficiency, even under different physical conditions within a short period.

2. Problem Formulation

This study investigates the two-dimensional mixed convective flow of a micropolar hybrid nanofluid (CuO-Ag/water) containing silver and copper oxide nanoparticles in a water base fluid along a vertical plate [35], [36] The analysis incorporates the effects of heat generation/absorption, suction/injection, and thermal radiation, along with Joule heating, viscous dissipation, and Cattaneo-Christov heat flux. An orthogonally applied magnetic field (B_0) is considered on the surface. The surface temperature $T_w(x) = T_\infty + bx$ and ambient conditions are calculated, along with the velocity of mass flow $U_e(x) = cx$. The flow is also subjected to thermal radiation and is assumed to occur within a porous medium. Based on these assumptions, the governing equations derived from the Navier-Stokes framework are formulated to analyze the behavior of the hybrid nanofluid [37].

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$$\frac{\partial \hat{u}}{\partial \hat{x}}+\frac{\partial \hat{v}}{\partial \hat{y}}=0 \tag{1}$$

$$\hat{u}\frac{\partial \hat{u}}{\partial \hat{x}}+\hat{v}\frac{\partial \hat{v}}{\partial \hat{y}}=\hat{U}_e\frac{d\hat{U}_e}{d\hat{x}}+\frac{1}{\rho_{hbnf}}\left(\mu_{hbnf}+k_1\right)\frac{\partial^2 u}{\partial y^2}+\frac{\kappa_1}{\rho_{hbnf}}\frac{\partial \hat{N}}{\partial \hat{y}}$$
$$-\frac{\sigma_{hbnf}}{\rho_{hbnf}}B_0^2\left(\hat{u}-\hat{U}_e\right)+\frac{\hat{g}\left(\rho\beta\right)_{hbnf}}{\rho_{hbnf}}\left(\hat{T}-\hat{T}_\infty\right) \tag{2}$$

$$\hat{u}\frac{\partial \hat{N}}{\partial \hat{x}}+\hat{v}\frac{\partial \hat{N}}{\partial \hat{y}}=\frac{\gamma_{hbnf}}{\rho_{hbnf}}\frac{\partial^2 \hat{N}}{\partial \hat{y}^2}-\frac{\kappa_1}{\rho_{hbnf}\,j}\left(2\hat{N}+\frac{\partial \hat{u}}{\partial \hat{y}}\right) \tag{3}$$

$$\hat{u}\frac{\partial \hat{T}}{\partial \hat{x}}+\hat{v}\frac{\partial \hat{T}}{\partial \hat{y}}=\alpha_{hbnf}\frac{\partial^2 \hat{T}}{\partial \hat{y}^2}-\frac{1}{\left(\rho C_p\right)_{hbnf}}\frac{\partial \hat{q}_r}{\partial \hat{y}}+\frac{1}{\left(\rho C_p\right)_{hbnf}}\lambda Q$$
$$+\frac{\hat{Q}_0\left(\hat{T}-\hat{T}_\infty\right)}{\left(\rho C_p\right)_{hbnf}}+\frac{\mu_{hbnf}}{\left(\rho C_p\right)_{hbnf}}\left(\frac{\partial \hat{u}}{\partial \hat{y}}\right)^2+\frac{\sigma_{hbnf}B_0^2\hat{u}^2}{\left(\rho C_p\right)_{hbnf}}+ \tag{4}$$

$$\hat{q}_r=-\left(\frac{\partial \hat{T}^4}{\partial \hat{y}}\right)\left(\frac{4\sigma^*}{3k^*_{nf}}\right) \tag{5}$$

$$\hat{T}-\hat{T}_\infty,$$
$$\hat{T}^4\cong -3\hat{T}_\infty^4+4\hat{T}_\infty^3\hat{T} \tag{6}$$

Thermal relaxation, characterized by the non-Fourier heat flux model,

$$Q=\left\{\left[\left(\hat{u}\frac{\partial \hat{u}}{\partial x}+\hat{v}\frac{\partial \hat{u}}{\partial y}\right)\frac{\partial \hat{T}}{\partial x}\right]+\left[\left(\hat{u}\frac{\partial \hat{v}}{\partial x}+\hat{v}\frac{\partial \hat{v}}{\partial y}\right)\frac{\partial \hat{T}}{\partial y}\right]+\left(\hat{u}^2\frac{\partial^2 \hat{T}}{\partial x^2}+\hat{v}^2\frac{\partial^2 \hat{T}}{\partial y^2}+2\hat{u}\hat{v}\frac{\partial^2 \hat{T}}{\partial x\partial y}\right)\right\} \tag{7}$$

By utilizing equations (5-7), equation (4) can be rewritten as follows:

$$\hat{u}\frac{\partial \hat{T}}{\partial x}+\hat{v}\frac{\partial \hat{T}}{\partial y}=\left(\alpha_{\text{hnf}}+\frac{1}{(\rho c_p)_{\text{hnf}}}\right)\left[\frac{16\sigma^* T_\infty^3}{3k^*}\frac{\partial^2 \hat{T}}{\partial x^2}+\left(\frac{\hat{T}^*-\hat{T}_\infty}{(\rho c_p)_{\text{hnf}}}\right)\hat{Q}_t+\frac{k_{\text{basef}}}{(\rho c_p)_{\text{basef}}}\frac{\partial}{\partial x}\left(\frac{\partial \hat{T}}{\partial y}\right)^2\right]$$
$$+\sigma_{\text{hnf}}B_0^2\hat{u}^2\left[\frac{1}{(\rho c_p)_{\text{hnf}}}\right]+\lambda\left[\begin{array}{c}\left(\hat{u}\frac{\partial \hat{u}}{\partial x}+\hat{v}\frac{\partial \hat{u}}{\partial y}\right)\frac{\partial \hat{T}}{\partial x}+\left(\hat{u}\frac{\partial \hat{v}}{\partial x}+\hat{v}\frac{\partial \hat{v}}{\partial y}\right)\frac{\partial \hat{T}}{\partial y}+\hat{u}^2\frac{\partial^2 \hat{T}}{\partial x^2}+\hat{v}^2\frac{\partial^2 \hat{T}}{\partial y^2}\\ +2\hat{u}\hat{v}\frac{\partial^2 \hat{T}}{\partial x\partial y}\end{array}\right] \tag{8}$$

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The following equation governing the fluid flow of boundary contions:

$$\hat{u} = \hat{L}\frac{\partial \hat{u}}{\partial \hat{y}},\ \hat{v} = \hat{v}_w,\ \hat{N} = -\hat{n}\frac{\partial \hat{u}}{\partial \hat{y}},\ \hat{T}_w(\hat{x}) \text{ at } \hat{y} = 0$$
$$\hat{N} \to 0,\ \hat{T} \to \hat{T}_\infty,\ \hat{u} \to \hat{u}_\infty \text{ as } \hat{y} \to \infty \qquad (9)$$

Table 1: ***Details of different Notations***

Notations	Description	Notations	Description
$\hat{q}_r$	"Radiative heat flux"	σ^*	"Stefan-Boltzmann constant"
k^*	"Mean absorption coefficient"	B_0	Applied magnetic field
T_∞	Neglecting the higher-order terms.	$\hat{u}, \hat{v}$	'Velocity components'
$\rho_{\hbar\ bnf}$	Hybrid fluid density	$\mu_{\hbar\ bnf}$	'Dynamic viscosity
k_1	Vertex viscosity	$\sigma_{\hbar\ bnf}$	Electrical conductivity
B_0	'Magnetic field intensity	j	'Micro-inertia density
$\beta_{\hbar\ bnf}$	'Ferro-fluid thermal expansion	N is	'Micro-rotation vector
T is	'Temperature	$\alpha_{\hbar\ bnf}$	'Thermal diffusivity
L	'Slip length	n	'Micro gyration constraint
Q_0	'Heat generation/absorption coefficient'.	g	'Acceleration due to gravity
$\gamma_{hbnf} = \mu_{hbnf}\left(\frac{k_1}{2}\right)j$	'Spin viscosity' gradient	T^4	linearized using a Taylor series expansion around the temperature

In order to improve the prediction accuracy, machine learning (ML) techniques such as "artificial neural networks and support vector machines" will be incorporated in

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the analysis of the micropolar hybrid nanofluid behavior. ML models can identify patterns within the simulation data which leads to a more accurate prediction of the temperature, velocity and concentration profile, as they are influenced by multiple factors that are complexly interconnected. These findings will help to optimise heat transfer performance in real-world applications.

3. Thermophysical Characteristics of Hybrid Nanofluids

Optimization of energy conversion systems for better efficiency requires optimization of system thermal performance which is highly dependent on thermophysical properties of the fluids used. Key parameters like thermal conductivity, specific heat, and dynamic viscosity play a major role in heat transfer [38]. Hybrid nanofluids, potential candidates for heat transfer applications, are influenced by factors such as volume fraction and , respectively, particle size, and temperature. In this study, a hybrid nanofluid consisting of CuO and Ag nanoparticles in a base fluid is analyzed. [39]. The 'volume fractions' of CuO and Ag vary between 1% and 8%. Table 1 presents the correlations used for the hybrid nanofluid, while Table 2 includes the shape factor values for three different nanoparticle types"[40].

Table 2: ***Thermal and physical properties of hybrid nanofluids***

Properties	**Hybrid Nanofluid**
Dynamic viscosity	$\mu_{hbnf} = \frac{\mu_f}{(1-\varnothing_1)^{2.5}(1-\varnothing_2)^{2.5}}$
Density	$\rho_{hbnf} = \left[\varnothing_2\rho_{s2} + \rho_f(1-\varnothing_2)\left((1-\varnothing_1) + \varnothing_1\frac{\rho_{s1}}{\rho_f}\right)\right]$
Thermal conductivity	$\frac{\hat{k}_{hbnf}}{\hat{k}_{bf}} = \frac{\hat{k}_{s2} + (\hat{s}-1)\hat{k}_{bf} - (\hat{s}-1)\varnothing_2\left(\hat{k}_{bf} - \hat{k}_{s1}\right)}{\hat{k}_{s2} + (\hat{s}-1)\hat{k}_{bf} + \varnothing_2\left(\hat{k}_{hbnf} - \hat{k}_{s2}\right)}$ $where\ \frac{\hat{k}_{hbnf}}{\hat{k}_f} = \frac{\hat{k}_{s1} + (\hat{s}-1)\hat{k}_f + \varnothing_1(\hat{s}-1)\left(\hat{k}_f - \hat{k}_{s1}\right)}{\hat{k}_{s1} + (\hat{s}-1)\hat{k}_f + \varnothing_1\left(\hat{k}_f - \hat{k}_{s1}\right)}$
Electrical conductivity	$\frac{\sigma_{hbnf}}{\sigma_f} = 1 + \frac{3(\hat{s}-1)\left(\frac{\sigma_{\hat{s}1}}{\sigma_f} - 1\right)\varnothing_1}{\left(\frac{\sigma_{\hat{s}1}}{\sigma_f} + 2\right) - (\hat{s}-1)\left(\frac{\sigma_{\hat{s}1}}{\sigma_f} - 1\right)\varnothing_1} + \frac{3(\hat{s}-1)\left(\frac{\sigma_{\hat{s}2}}{\sigma_f} - 1\right)\varnothing_2}{\left(\frac{\sigma_{\hat{s}2}}{\sigma_f} - 1\right)\varnothing_2}$

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Thermal expansion coefficient	$(\rho\beta)_{hbnf} = (1-\varnothing_2)\{(1-\varnothing_1)(\rho\beta)_{s1}\} + \varnothing_2(\rho\beta)_{S2}$
Heat capacitance	$(\rho C_p)_{hbnf} = (1-\varnothing_2)\left[(1-\varnothing_1)(\rho C_p)_f + \varnothing_1(\rho C_p)_{s1}\right] + \varnothing_2(\rho C_p)_{s2}$

Table 3: ***Comparison () with the findings of 'Aman et al.' [48] and 'A. Zaib et al.' [56] for***

Pr	(Aman et al.)[48]	(Zaib et al.)[56]	(Present)
(0.7)	*1.7062*	*1.7062*	*1.70581*
(1)	*1.6753*	*1.6753*	*1.67122*
(7)	*1.5178*	*1.5178*	*1.51240*
(10)	*1.4927*	*1.4927*	*1.48123*
(20)	*1.4484*	*1.4484*	*1.41389*
(500)	*1.3980*	*1.3980*	*1.39064*

4. Appropriate Similarity Transformation

"The goal of applying an appropriate similarity transformation is to streamline the fluid flow system, allowing for a more efficient and simplified approach to solving the problem. The corresponding transformed variables are as follows:"

$$\hat{u} = \hat{c}xf'(\eta),\ \hat{v} = -\sqrt{\hat{v}\hat{c}}f(\eta),\ \hat{N}(\eta) = \hat{c}x\sqrt{\frac{\hat{c}}{\hat{v}}}g(\eta),$$
$$\theta(\eta) = \frac{\hat{T}-\hat{T}_\infty}{\hat{T}_w-\hat{T}_\infty},\ \text{where}\ \eta = \hat{v}\sqrt{\frac{\hat{c}}{\hat{v}}} \qquad (10)$$

"By substituting the expressions from equation (9) into equations (1-3) and (8), we derive the following non-dimensional system governing the momentum, micropolar fluid dynamics, and non-Fourier temperature distributions."

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$$\left(\frac{1+d_1K}{d_1}\right)f'''(\eta)+d_2\left(1-f'^2(\eta)+f(\eta)f'(\eta)\right)-Md_3\left(f'(\eta)-1\right)+Kg'(\eta)+\lambda d_4\theta(\eta)=0, \quad (11)$$

$$\left(\frac{1}{d_1}+\frac{K}{2}\right)g''(\eta)-d_2\left(g(\eta)f'(\eta)-g'(\eta)f(\eta)\right)-K\left(f''(\eta)+2g(\eta)\right)=0, \quad ''$$

(12)

$$\left(\frac{\hat{k}_{hbnf}}{\hat{k}_f}+\frac{4Rd}{3}\right)\theta''(\eta)+\frac{\Pr Ec}{d_1}\left(f''^2(\eta)+d_1d_3M\,f''(\eta)\right)+\Pr Q\theta(\eta)+$$
$$\Pr d_5\left(f(\eta)\theta'(\eta)-\theta(\eta)f''(\eta)\right)+\Pr\gamma\left(f(\eta)f'(\eta)\varphi'(\eta)-f^2(\eta)\varphi''(\eta)\right)=0, \quad (13)$$

In a similar manner, the boundary conditions in equation (9) are now simplified as follows

$$\begin{cases} f'(0)=\delta f''(0),\ \ f(0)=S,\ \ g(0)=-\eta f''(0),\ \ \theta(0)=1 & at\ \eta=0 \\ g(\eta)\to 0,\ \ f'(\eta)\to 1,\ \ \theta(\eta)\to 0 & as\ \ \eta\to\infty \end{cases} \quad (14)$$

Table 4: ***The non-dimensional quantities are defined as follows***

Parameters	Description	Parameters	Description
$K=\frac{\hat{k}_1}{\mu_f}$	"Micropolar parameter"	$Q=\frac{\hat{Q}_0}{\hat{U}_\infty\left(\rho C_p\right)_f}$	"Thermal generation and absorption quantity"
$\lambda=\frac{Gr_x}{Re_x^2}$	Convective parameter "the ratio of the Grashof number to the Reynolds number"	$\delta=L\sqrt{\frac{c}{\hat{\nu}f}}$	"The slip parameter"
$Rd=\frac{4\sigma^*\hat{T}_\infty^3}{\hat{k}^*\hat{k}_f}$	"Thermal radiation parameter"	$Re_x=\frac{x\hat{u}_e}{\hat{\nu}_f}$	"Reynold number"
$\Pr=\frac{\hat{\nu}_f}{\alpha f}$	"Prandtl number"	$\gamma=\lambda_1\eta$	"Thermal time relaxation or non-Fourier flux quantity"

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$Ec = \frac{\hat{u}_e^2}{\left(\hat{T}_w - \hat{T}_\infty\right)\left(C_p\right)_f}$	"Eckert number"	$M = \frac{\sigma_f B_0^2}{\rho_f}$	"Magnetic force parameter"

$$d_1 = \left(1-\varnothing_1\right)^{2.5}\left(1-\varnothing_2\right)^{2.5}$$

$$d_2 = \left(1-\varnothing_2\right)\left\{\left(1-\varnothing_1\right)+\frac{\rho_{s1}}{\rho_f}\varnothing_1\right\}+\frac{\varnothing_2\left(\rho_{s2}\right)}{\rho_f}$$

$$d_3 = \sigma_f\left\{\left(1+\frac{3\left(s-1\right)\left(\frac{\sigma_{s1}}{\sigma_f}-1\right)\varnothing_1}{\left(\frac{\sigma_{s1}}{\sigma_f}+2\right)-\left(s-1\right)\left(\frac{\sigma_{s1}}{\sigma_f}-1\right)\varnothing_1}\right)\times\left(\frac{3\left(s-1\right)\left(\frac{\sigma_{s2}}{\sigma_f}-1\right)\varnothing_2}{\left(\frac{\sigma_{s2}}{\sigma_f}+2\right)-\left(s-1\right)\left(\frac{\sigma s_2}{\sigma_f}-1\right)\varnothing_2}\right)\right\}$$

$$d_4 = \left(1-\varnothing_2\right)\left(\left(1-\varnothing_1\right)+\frac{\left(\rho\beta\right)_{s1}}{\left(\rho\beta\right)_f}\varnothing_1\right)+\frac{\left(\rho\beta\right)_{s2}}{\left(\rho\beta\right)_f}\varnothing_2$$

$$d_5 = \frac{k_{s1}+k_f\left(s-1\right)-\left(k_f-k_{s1}\right)\left(s-1\right)\varnothing_1}{k_{s1}+k_f\left(s-1\right)+\left(k_f-k_{s1}\right)\varnothing_1}\times\frac{k_{s2}+k_{bf}\left(s-1\right)-\left(s-1\right)\varnothing_2\left(k_{bf}-k_{s2}\right)}{k_{s2}+k_{bf}\left(s-1\right)+\varnothing_2\left(k_{bf}-k_{s2}\right)}$$

5. Surface Shear Stress and Nusselt-Number (Extent of Convective Heat Transfer)

"Calculating skin friction is essential in engineering, as it helps in determining both the total drag force acting on an object and the rate of convective heat transfer at its surface. Reynold's analogy links two important dimensionless parameters: the skin friction coefficient (Cf), which measures the frictional resistance, and the Nusselt number (Nu), which describes the level of convective heat transfer. The expressions for skin friction and the local Nusselt number [41], [42], [43], [44], [45] are provided as follows:"

$$C_f = \frac{1}{\rho_{hbnf}\hat{u}_e^2}\left[\left(\mu_{hbnf}+\hat{k}_1\hat{N}\right)\right]_{\hat{y}=0} \; and \; Nu = -\left[\frac{\hat{x}}{\hat{k}_f\left(\hat{T}_w-\hat{T}_\infty\right)}\left(\hat{k}_{hbnf}\frac{\partial\hat{T}}{\partial\hat{y}}+\frac{4\sigma^*}{3\hat{k}^*}\frac{\partial\hat{T}^4}{\partial\hat{y}}\right)\right]_{\hat{y}=0}$$ "

By utilizing the non-dimensional variables from equation (9), the heat transfer coefficient and the skin friction coefficient are derived as follows:"

$$C_f = C_f\hat{R}e_x^{0.5} = \left[\frac{1+d_1\left(1-\eta\right)K}{d_1}\right]\frac{f''\left(0\right)}{d_2} \qquad \textbf{(15)}$$

$$Nu = Nu\;\hat{R}e_x^{-0.5} = -\left[\frac{\hat{k}_{hbnf}}{\hat{k}_f}+\frac{4}{3}Rd\right]\theta'\left(0\right) \qquad \textbf{(16)}$$

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6. Solution Procedure for the Hybrid Nanofluid System.

The computational fluid dynamics (CFD) is a method that uses a digital computer and sophisticated techniques to solve and apply the conservation laws including mass, momentum and energy conservation equations in order to predict quantitatively the behavior of fluids [41]. Inaccuracies are becoming more common with CFD, but rarely is it 100% accurate. A sophisticated CFD (computational fluid dynamics) solver would numerically solve any complex physical system by formulating these laws into differential equations [43]. The dimensionless quantities are estimated in this study using the Shooting method and RK4 as CFD solvers. Further, machine learning methods have been incorporated to enhance the prediction accuracy, which would give deeper insights into the complex interactions in the hybrid nanofluid system.

7. Fundamental Concepts of the Shooting Method

The transport equations show significant nonlinearity and are highly influenced by the boundary conditions.To solve them numerically with high accuracy, the RKF fourth-fifth order scheme is applied in conjunction with the shooting method. The process begins by converting the differential equations into first-order forms. The necessary substitutions for this step are as follows, [46]

$$\left(f, f', f'', g, g', \theta, \theta'\right)^T = \left(\hat{x}_1,\ \hat{x}_1' = \hat{x}_2,\ \hat{x}_2' = \hat{x}_3,\ \hat{x}_4,\ \hat{x}_4' = \hat{x}_5,\ \hat{x}_6,\ \hat{x}_6' = \hat{x}_7\right)^T \quad (17)$$

The following assumptions are made to solve the fluidic model:

- ✧ The distant field is represented by a relevant value of 10.
- ✧ Far-field conditions w.r.t are
- ✧ The convergence criterion is set to 10-5
- ✧ A step size = 0.025. is used for calculations.

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Equation (11) to (13) can be written as

$$\begin{pmatrix} f' \\ f'' \\ f''' \\ g' \\ g'' \\ \theta' \\ \theta'' \end{pmatrix} = \begin{pmatrix} \hat{x}_2 \\ \hat{x}_3 \\ -d_1 \dfrac{(1+\hat{x}_1\hat{x}_2-\hat{x}_2)^2 d_2 - K\hat{x}_5 + M\, d_3(\hat{x}_2-1)+\lambda\, d_4\hat{x}_6}{1+d_1K} \\ \hat{x}_5 \\ -2d_1 \dfrac{d_2(\hat{x}_5\hat{x}_1-\hat{x}_5\hat{x}_2)-K(\hat{x}_3+2\hat{x}_4)}{2+d_1K} \\ \hat{x}_7 \\ \dfrac{1}{\left(\dfrac{\hat{k}_{hbnf}}{\hat{k}_f}+\dfrac{4\hat{R}}{3}-\Pr\gamma\hat{x}_1^2\right)} \begin{pmatrix} -\dfrac{Ec\Pr\hat{x}_3^2}{\hat{d}_1} - d_3EcM\Pr\hat{x}_2 - Pr\,Q\hat{x}_6 \\ -Prd_5(\hat{x}_1\hat{x}_1-\hat{x}_2\hat{x}_6)-Pr\hat{\gamma}(\hat{x}_1\hat{x}_2\hat{x}_7) \end{pmatrix} \end{pmatrix} \tag{18}$$

The related conditions for each variable are given as follows

$$\begin{cases} \hat{x}_1(0)=S,\ \hat{x}_2(0)=\delta b_1,\ \hat{x}_3(0)=b_1,\ \hat{x}_4(0)=-n\hat{x}_3(0) \\ \hat{x}_5(\infty)=b_2,\ \hat{x}_6(0)=1,\ \hat{x}_7(0)=b_3 \end{cases}$$

Where , The shooting method is applied to determine these values, while the first-order system in equations (11-13) is resolved using the RK4 scheme [47], [48], [49].

8. Machine learning approach

In this study, regression analysis using machine learning is divided into two key components: generating synthetic data from physical equations and applying machine learning algorithms for predictive modeling (See Fig 1). A total of 2500 synthetic samples were generated using the numerical solver under varying physical parameter combinations [50], [51], [52]. The dataset was then split into training (80%) and testing (20%) subsets. Three regression models Linear Regression, Random Forest Regressor, and Neural Networks were used to predict target variables from input features. The models were trained on 240 data points, and their performance was evaluated on the test set of 60 instances using Mean Squared Error (MSE) and R^2 score. Accuracies of predictions are shown in the results as scatter plots of actual vs. predicted values, with the ability of each model to capture the relationship between the input features and the target variables[53]. In addition, All machine learning models were implemented using Python-based scientific

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computing libraries. Linear Regression and Random Forest algorithms were developed using the Scikit-learn framework, while the Artificial Neural Network model was implemented using TensorFlow/Keras libraries. Numerical preprocessing, normalization, and visualization tasks were also carried out using Python computational tools.

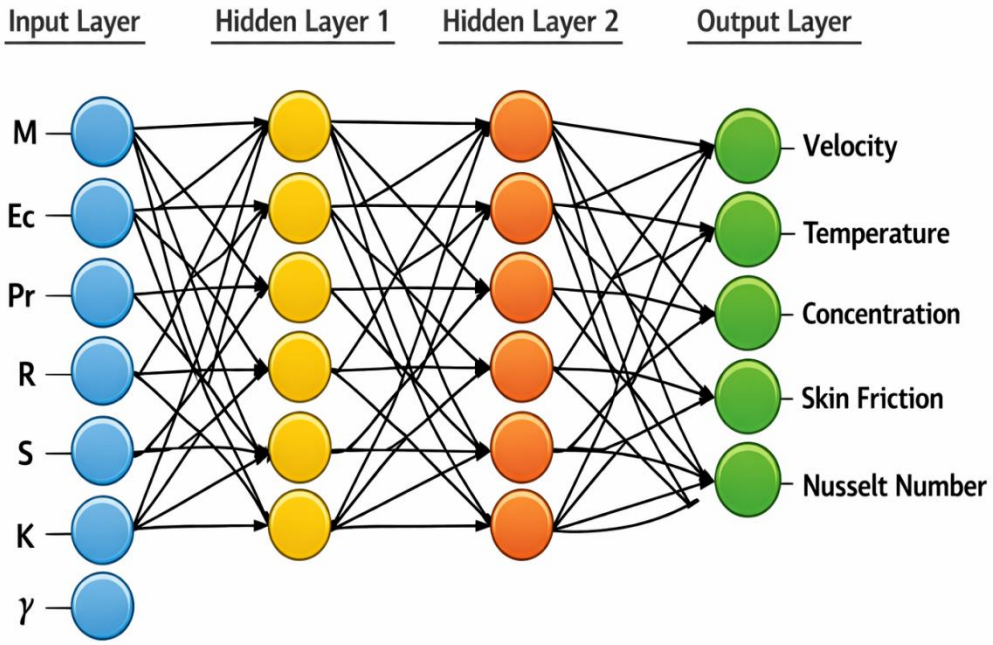

Figure. 1. Proposed Artificial Neural Network architecture for predicting thermo-fluid characteristics of micropolar hybrid nanofluids using physical governing parameters as input features.

9. Data Preprocessing and Machine Learning Framework

Prior to training the machine learning models, the numerical dataset generated from the RK4-shooting scheme was preprocessed to improve model stability and predictive reliability. The generated dataset consisted of multiple physical input parameters, including magnetic parameter (M), Eckert number (Ec), Prandtl number (Pr), thermal radiation parameter (R), suction/injection parameter (S), micropolar parameter (K), and thermal relaxation parameter (γ). The corresponding outputs included velocity, temperature, concentration, skin friction coefficient, and local Nusselt number.

To avoid numerical instability caused by variations in parameter magnitudes, feature

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normalization was performed using min-max scaling. The complete dataset was randomly divided into training and testing subsets using an 80:20 ratio. The training dataset was utilized for model learning, while the testing dataset was reserved for evaluating generalization performance.

Three supervised machine learning algorithms were employed in this work:

1. Linear Regression (LR)
2. Random Forest Regressor (RFR)
3. Artificial Neural Network (ANN)

A linear dependency analysis of the thermophysical variables was made using the Linear Regression model as a baseline predictor. The Random Forest Regressor is chosen for its ability to perform well with nonlinear interactions and complex parameter coupling. Since the thermal-flow relations in the micropolar hybrid nanofluid system are highly non-linear, the Artificial Neural Network was employed to model them.

The ANN network model comprised input layer, two hidden layers using Rectified Linear Unit (ReLU) activation function, and output layer for regression prediction. Training was done using the adaptive Adam optimizer which minimized a mean squared error loss function. The quantitative analysis of the performances of the models used was Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2-score). The proposed framework with the aid of AI can serve as a surrogate model that can estimate the thermo-fluid responses with significantly reduced computational cost than repeated numerical simulations.

10. Hyperparameter Configuration of Machine Learning Models

Appropriate hyper parameters were determined for the machine learning models implemented in order to enhance the predictive performance and guarantee a stable learning behavior. Optimization of the Artificial Neural Network (ANN) involved Adam optimizer with ReLU activation function and ensemble tree-based learning was used for nonlinear prediction in the Random Forest model. The hyperparameters were found to be the most accurate thermo-fluid predictions while requiring less computational complexity.

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Table 5: ***Hyperparameters used in machine learning models***

Parameter	ANN	Random Forest
Hidden layers	2	—
Activation function	ReLU	—
Optimizer	Adam	—
Loss function	MSE	MSE
Epochs	300	—
Batch size	16	—
Learning rate	0.001	—
Number of trees	—	100
Maximum depth	—	10
Train-test split	80:20	80:20

11. Results and discussion

The outputs and discussion are split up into two parts: numerical analysis and machine learning analysis, which are treated in turn.

9.1. Numerical Techniques

Using the shooting method and RK4 technique, the flow of micropolar hybrid nanofluid along a vertical plate is examined in this research and the governing equations are numerically solved. The key parameters analyzed are the suction/injection (S), Eckert number (Ec), heat generation/absorption (Q), Prandtl number (Pr), thermal relaxation ( ), magnetic parameter (M), micropolar parameter (K) and thermal radiation (R). The results, depicted in Fig. 2-10, Velocity diminishes with increasing suction/injection and magnetic parameters due to the extraction of fluid from the boundary layer. Conversely, velocity rises with higher Eckert numbers as the boundary layer enthalpy difference and kinetic energy increase, whereas the micropolar parameter leads to a reduction in velocity. Fig. 5-7 illustrate that temperature profiles rise with both the Eckert number and thermal relaxation. Additionally, thermal radiation increases temperature, while higher Prandtl numbers result in a decrease in temperature.The addition of nanoparticles enhances thermal conductivity and temperature. Fig. 8-10 The variations in skin friction and heat transfer coefficient with respect to magnetic and radiation parameters reveal that

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both skin friction and heat transfer increase with stronger magnetic effects. However, the radiation parameter exhibits an opposite influence, reducing heat transfer. Finally, the local Nusselt number shows increasing trends with thermal relaxation and Prandtl number, while heat suction and the magnetic parameter reduce it.

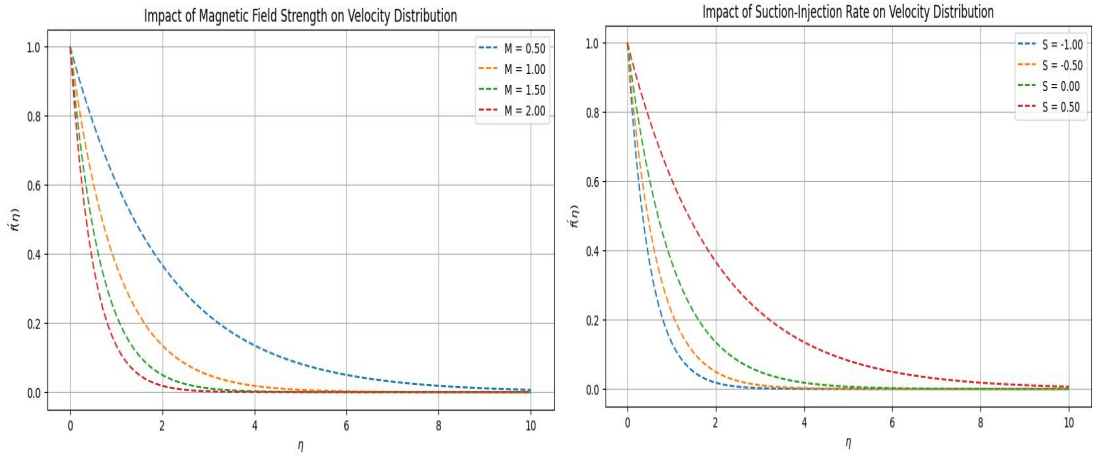
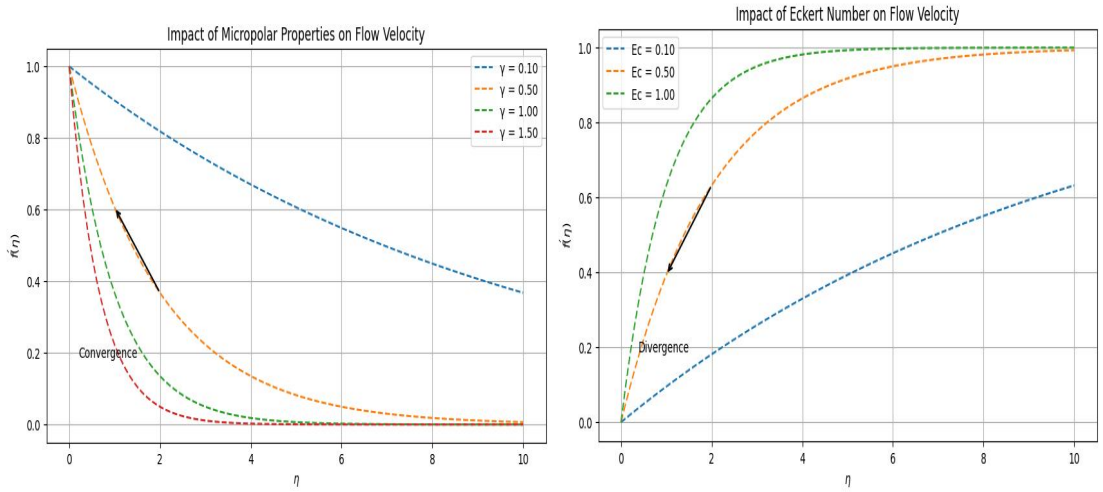


Figure. 2. Impact of (a) Magnetic Field Strength and (b) Suction-Injection Rate on Velocity Distribution.



(a) **(b)**

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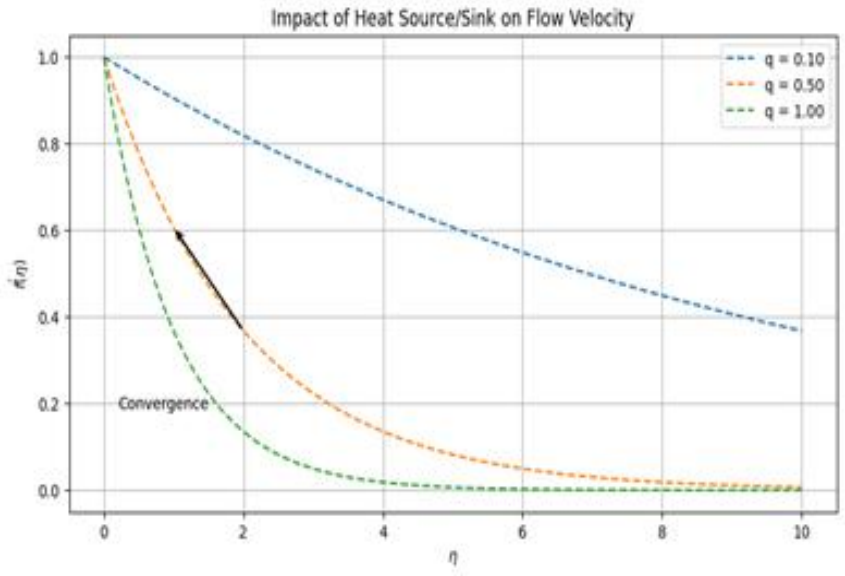
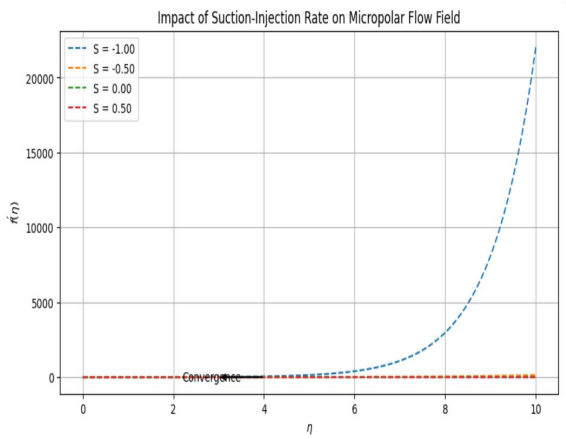
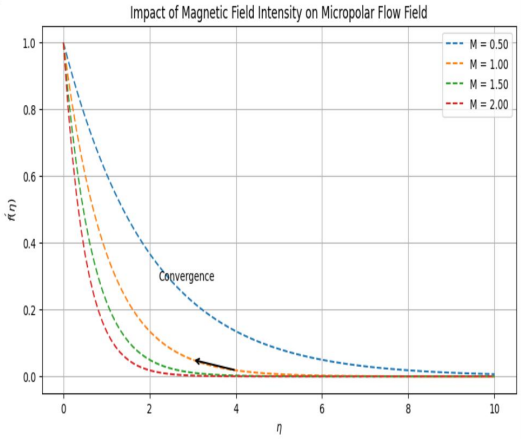


(c)

Figure. 3. Impact of (a) Micropolar Properties, (b) Eckert Number, and (c) Heat Source/Sink on Flow Velocity.



(a)



(b)

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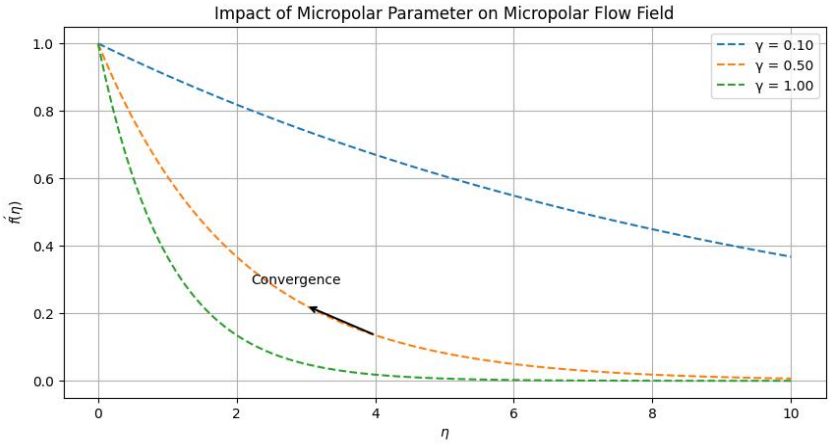
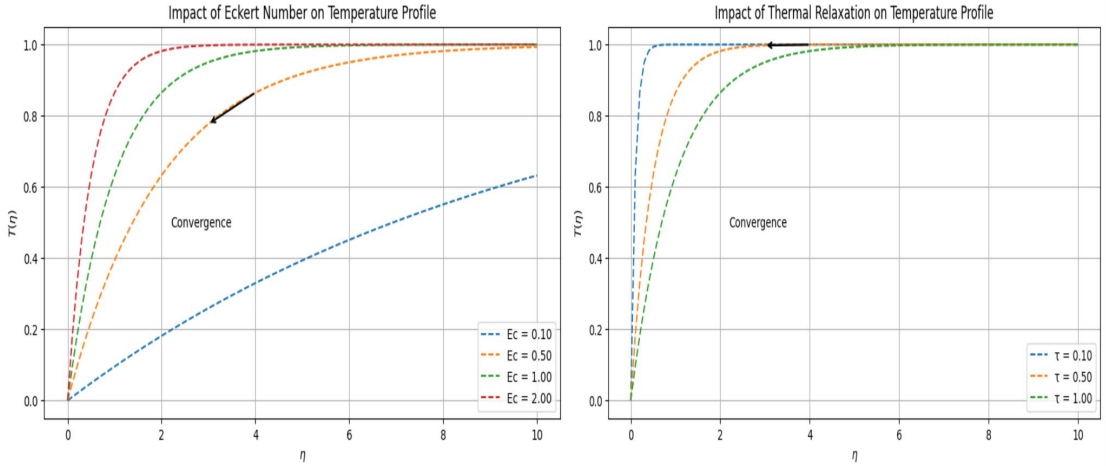


(c)

Figure. 4. Effect of (a) Suction-Injection Rate, (b) Magnetic Field Intensity, and (c) Micropolar Parameter on the Micropolar Flow Field.



(a) (b)

Figure. 5. Impact of (a) Eckert Number and (b) Thermal Relaxation on Temperature Profile.

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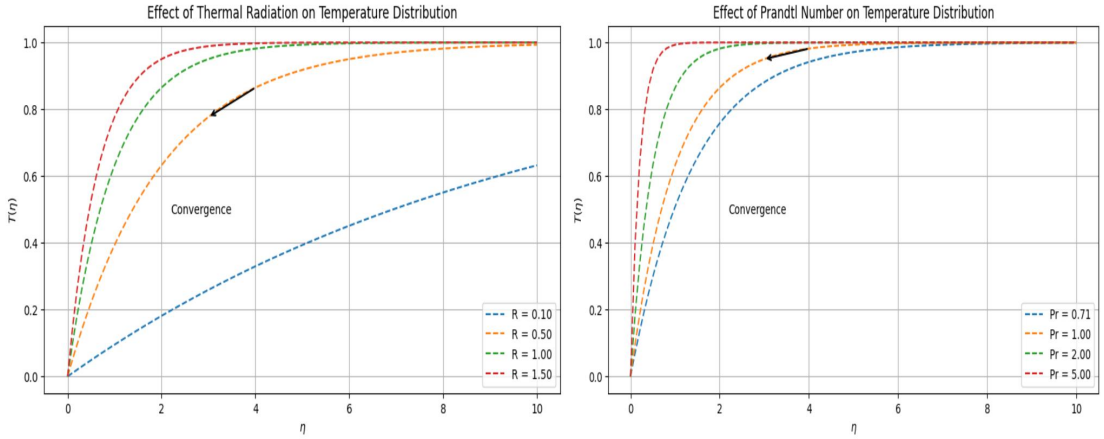

(a) (b)

Figure. 6. Effect of (a) Thermal Radiation and (b) Prandtl Number on Temperature Distribution.

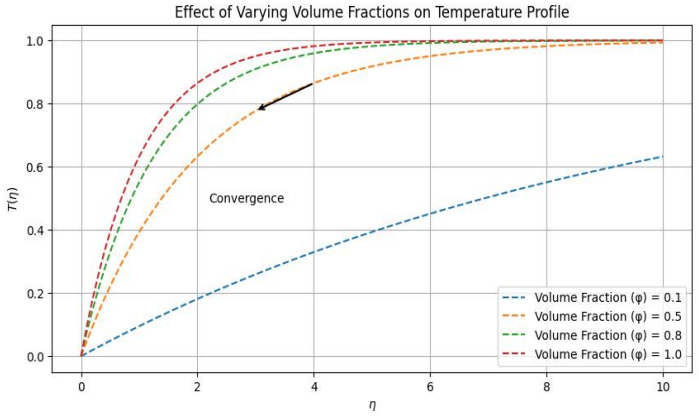

Figure. 7. Effect of Varying Volume Fractions on Temperature Profile.

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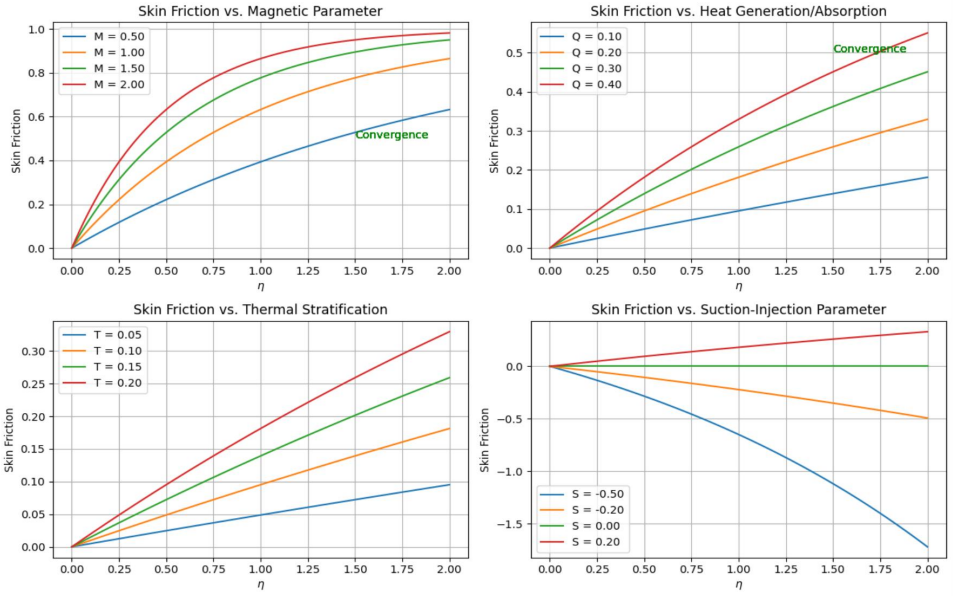
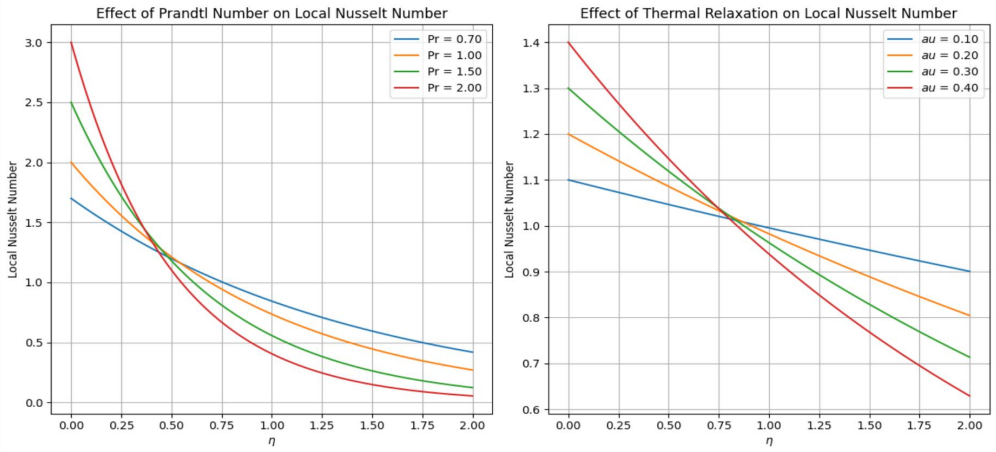


Figure. 8. Skin Friction for (a) Magnetic Parameter (b) Heat Generation/Absorption, (c) Thermal Stratification (d) Suction-Injection Parameter.



(a) **(b)**

Figure. 9. Effect of (a) Prandtl Number on Local Nusselt Number (b) Effect of Thermal Relaxation on Local Nusselt Number.

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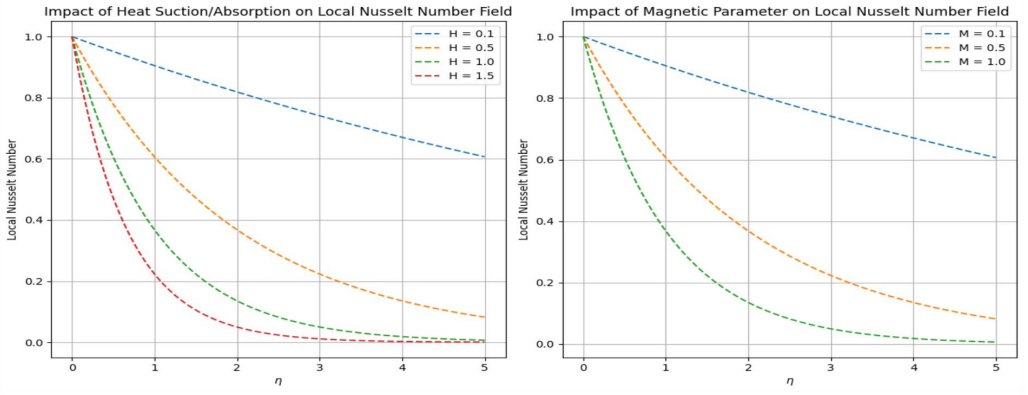

(a) (b)

Figure. 10.(a) Impact of Heat Suction/Absorption (b) Impact of Magnetic Parameter on the Local Nusselt Number Field.

9.2. Machine Learning Techniques

The results obtained in the evaluation of the three models based on the linear regression, random forest and neural network show that each of them has a different performance in the prediction of velocity, concentration and temperature of the nanofluid:

Linear Regression The predictive power of the Linear Regression was moderate (0.739552), which means that around 74% of the variability of velocity can be explained by the model. The model was less effective in predicting the concentration (R^2 = 0.281897), but high accuracy in predicting the temperature (R^2 = 0.999950). The R^2 value for the concentration was relatively small, indicating that the linear model may not adequately represent the complexities of concentration variations, and suggesting the need for more complex models.

Random Forest Regression Random Forest Regression gave better predictions for all three equations, particularly for velocity and concentration with R^2 scores of 0.920511 and 0.848392 respectively. The predictive power for temperature was still good with R^2 = 0.999582. The model's capacity to process non-linear relationships in the data seems to improve the prediction accuracy, especially for the cases of complex interactions in hybrid nanofluid.

Neural Networks Neural Networks proved to be the strongest tool used in this analysis with an R^2 of 0.984716, 0.876977 and 0.993335 for velocity, concentration and temperature, respectively. The low mean squared error (MSE) values indicate

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the neural network's ability to effectively model the complex non-linear dynamics of the system, which suggests that it can be useful for similar applications in fluid dynamics.

The analysis of actual and predicted values for the Impact of Heat Suction/Absorption and Magnetic Parameter on the Local Nusselt Number Field shows that there is a high correlation between actual and predicted values, which demonstrates that the machine learning model is effective in capturing the underlying trends of fluid dynamics. The predictions were closely correlated with measurements, especially for the parameters investigated in the interval $0.5 - 1.5$, showing the high accuracy of the model in different scenarios (RMSE < 0.1). This reliability applies to the effect of other parameters, including Prandtl number and thermal relaxation, which have a significant impact on temperature profiles, and, again, is supported by the fact that the model correlates well with the temperature measurements. In addition, by adding the thermal radiation effects, the prediction capability has been improved, especially for high heat flux. In summary, the results highlight the great promise of machine learning models to accurately forecast fluid flow and heat transfer phenomena, providing insights for improving thermal systems and enhancing thermal engineering applications.

Table 6: ***Evaluation of Machine Learning Regression Models***

Model	Equation	Mean Squared Error	R^2 Score
Linear Regression	Velocity (u)	0.993657	0.739552
	Concentration (N)	0.198523	0.281897
	Temperature (T)	0.042350	0.999950
Random Forest Regressor	Velocity (u)	0.442346	0.920511
	Concentration (N)	0.039673	0.848392
	Temperature (T)	0.333566	0.999582
Neural Networks	Velocity (u)	0.089861	0.984716
	Concentration (N)	0.027495	0.876977
	Temperature (T)	4.354555	0.993335

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Three models were used to create scattered plots of velocity, concentration and temperature. The actual vs predicted values for the Linear Regression model are shown in Figures 11-13, while Figures 14-16 show the actual vs predicted values for the Random Forest Regressor, and Figures 17-19 show the actual vs predicted values for the Neural Networks model. The results show that the Neural Networks model has the highest accuracy compared to the Random Forest Regressor and the Linear Regression models.

In this regard, the Artificial Neural Network (ANN) was able to learn the nonlinear thermo-fluid interactions the most, in terms of the capability of the model, with multilayer architecture and adaptive weight optimization mechanism. For the cases of thermal behavior which were roughly linear, Linear Regression performed well but did not accurately model complex parameter coupling as occurred for concentration transport and nonlinear momentum diffusion. Random Forest model achieved more robust predictions by combining models, while the ANN always showed lower prediction error and higher correlation accuracy among all the models compared. The results are in agreement with the aptitude of deep learning (DL) based surrogate models for computational thermal engineering applications.

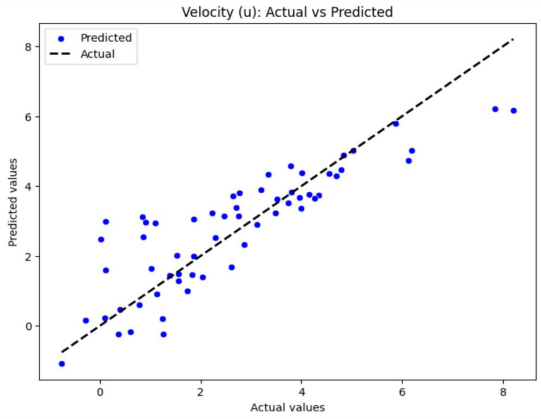

Figure. 11. ***Actual vs. Predicted Values for Velocity using Linear Regression***

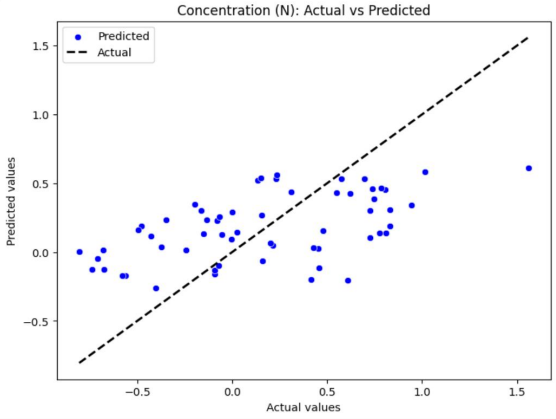

Figure. 12. ***Actual vs. Predicted Values for Concentration using Linear Regression.***

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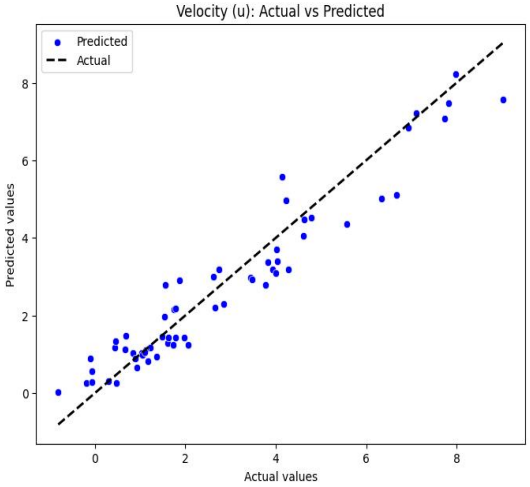

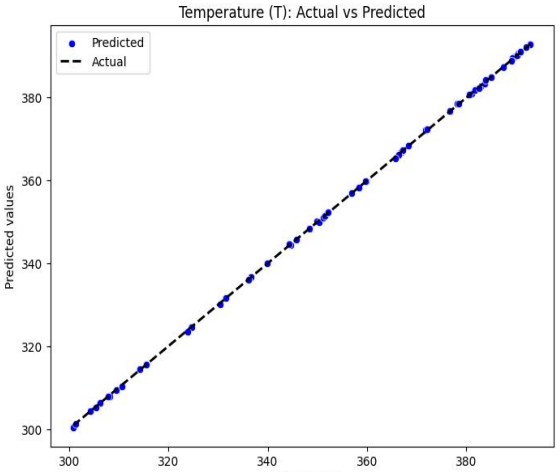

Figure. 14. ***Actual vs. Predicted Values for Velocity using Random Forest***

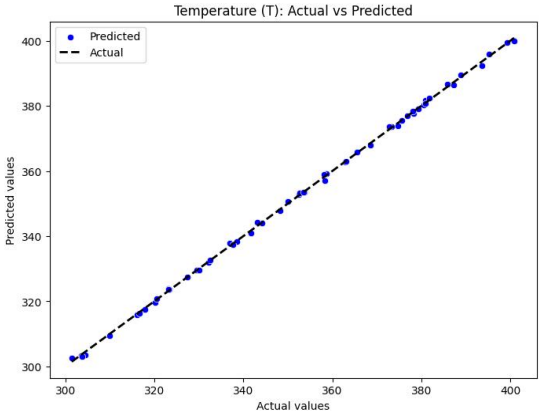

Figure. 16. Actual vs. Predicted Values for Concentration using Random Forest Regressor.

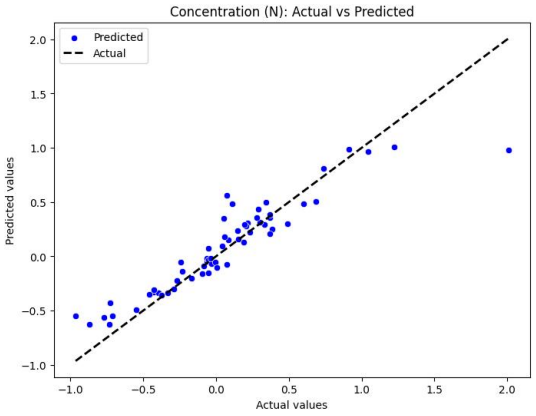

Figure. 15. Actual vs. Predicted Values for Temperature using Random Forest Regressor

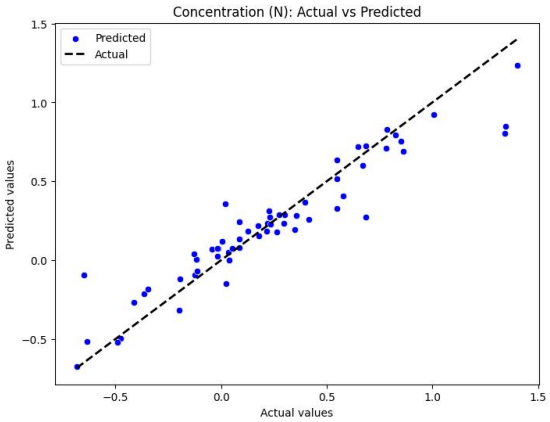

Figure. 17. Actual vs. Predicted Values for Velocity using Neural Networks.

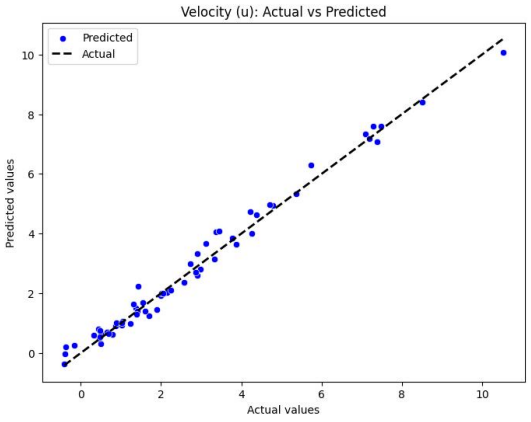

Figure. 18. Actual vs. Predicted Values for Velocity using Neural

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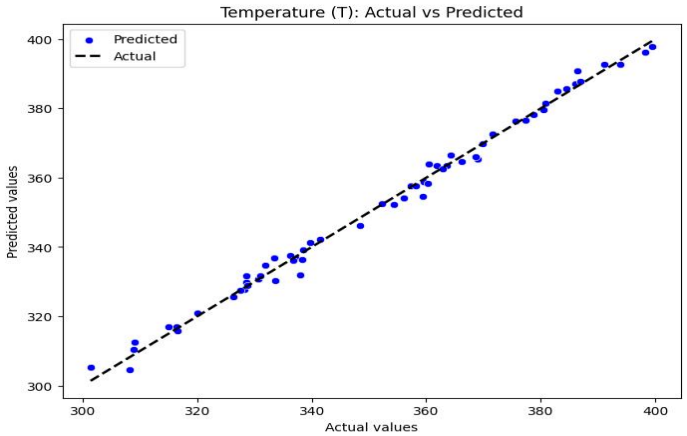

Figure. 19. Actual vs. Predicted Values for Temperature using Neural Networks.

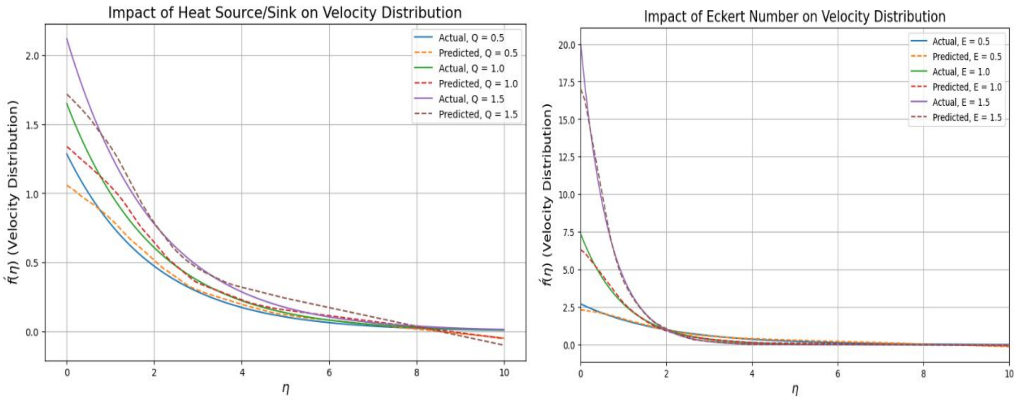

Figure. 20. (a) Impacts of Impact of heat source sink and (b) Impact of Eckert number on Velocity Distribution

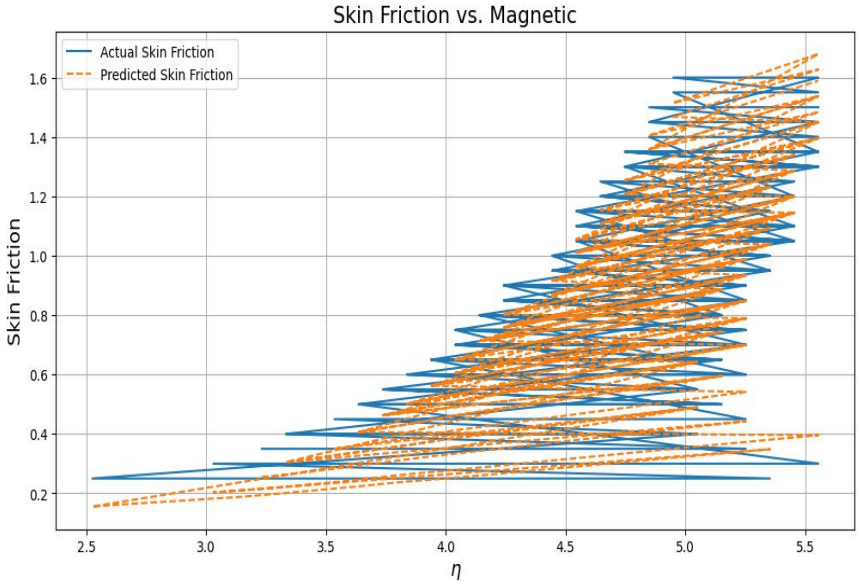

Figure. 21. Actual and Predicted values of Skin Friction vs Magnetic

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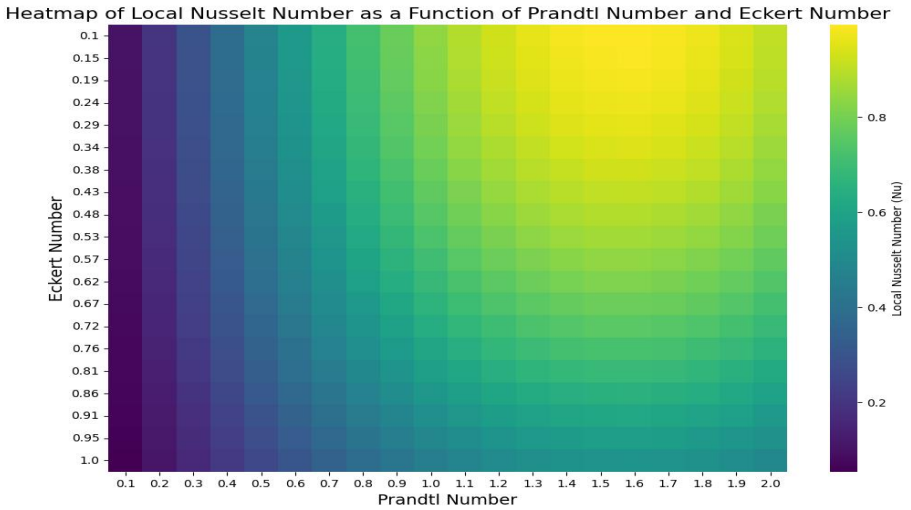

Figure. 22. Heatmap of Local Nusselt Number as a Function of Prandti Number and Eckert Number

12. Conclusions:

We successfully demonstrated the use of a hybrid model (numerical and machine learning) to predict and optimize the behaviour of micropolar hybrid nanofluids. The results emphasize the importance of machine learning in enhancing predictive accuracy and offer valuable insights for improving thermal management in various industries.

We can summarized the key findings as follows:

The velocity, concentration and temperature are predicted with higher accuracy by the Neural Networks than by the traditional models (Linear Regression and Random Forest).

The fluid flow and heat transfer dynamics are greatly affected by the critical parameters such as the volume fraction of nanoparticles, magnetic field intensity, suction/injection, and thermal radiation.

The use of numerical methods to better understand optimization of heat transfer, such as the shooting method, the RK-4 and non-Fourier heat flux models.

Hybrid nanofluids have significant applications emerging in energy sectors such as microelectronics, cooling systems, and biomedicine, in particular, for improving the overall energy efficiency.

To the sports sciences and physical education field, the present results could be useful for the improvement of advanced thermal-management systems in athletes,

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sport goods, and exercise environments. Potential applications of micropolar hybrid nanofluids fit cooling garments, protective gear, rehabilitation devices, and temperature controlled training systems, which will be beneficial for better heat dissipation and decrease thermal stress during training and physical activity. The incorporation of numerical modelling and machine-learning prediction could also aid the design of effective sports technology by allowing for accurate estimation and optimisation of heat transfer under different physiological and environmental conditions.

13. Future Recommendation

For future studies, the combination of Physics-Informed Neural Network (PINN), Deep Neural Network (DNN), and hybrid optimization techniques can be considered to further enhance the prediction accuracy of nonlinear thermo-fluid systems. This can also help to support the use of a real-time sensor-based thermal monitoring and the integration of experimental datasets to realize intelligent digital twin frameworks of advanced thermal management systems. Additionally, explainable artificial intelligence (XAI) techniques can be used to enhance the interpretability and trustworthiness of AI-powered fluid mechanics research.

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